Precoder Optimization with Local and Shared CSI on the K-user MIMO Interference Channel

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Abstract—**Network MIMO provides significant gains compared to transmission schemes based on the interference channel in cellular networks. However, the interference channel is adopted very often in particular due to data sharing limitations of network MIMO. These limitations are due to backhaul links which have finite capacity and also introduce delay. In interference channels, even though data is not exchanged between the transmitters, the global channel state information (CSI) needs to be shared in order to attain the degrees of freedom (DoF) of the channel. This highlights the necessity of reducing the amount of CSI exchange and relying more on local CSI to design the precoders in particular when the local CSI is accurate. In this contribution, cellular downlink transmission using time division duplexing (TDD) is considered where the base stations (BS) can estimate their own channels through reciprocity during the uplink phase. The interfering BSs share their channel estimates via backhaul links of finite capacity. We propose a distributed precoding method based on interference alignment (IA) which is shown to require relatively less CSI exchange compared to other methods.**

I. Introduction

Interference alignment (IA) has been proven to achieve the optimal degrees of freedom (DoF) over the interference channel. [1] formally brings IA to the picture while leaving a lot of questions about its practicality. Due to the promised benefits of this method, it has sparked a lot of research activities in recent years. As this scheme is based on the assumption of availability of global channel state information (CSI) at every transmitter, it is very likely that conventional CSI feedback implementations would fail to unveil the potential gains promised by IA. Another limitation is that even with perfect CSI, at low signal-to-noise-ratio (SNR), this scheme is highly suboptimal since the precoders are designed only based on the interfering channels and the direct channels are ignored.

Considering CSI feedback (that is never perfect in reality), IA is not optimal and the rate saturates due to the leakage introduced by channel mismatch which increases as the transmit power of the interferers increase. Simple time-sharing outperforms IA at high SNR with limited CSI feedback. However middle-range SNR might be of practical interest for implementation of IA if CSI feedback is efficiently designed to be sufficiently accurate.

In the medium SNR range, methods based on performance metrics like sum-rate optimization or mean-squared-error (MSE) minimization are more desirable since they exploit and balance the effect of both interfering channels and direct channels in a meaningful way [2]–[4]. In such methods the drawback is the requirement of all channel states (also the direct channels) at all the transmitters to compute an identical solution similar to a centralized processing. More liable to distributed implementation are the iterative schemes proposed in [5], [6]. These papers consider downlink precoder design where the transmitters can acquire information about their outgoing channels (denoted by local CSI) from the uplink transmission phase by reciprocity. However their proposed schemes still require some feedback from the receivers at each iteration. With this local CSI assumption, authors in [7] propose an algorithm which improves the sum-rate performance compared to IA in a single-stream setting. However their scheme also requires feedback from the receivers at every iteration.

In this paper, we consider the local CSI model where every node has access to some local perfect CSI (including its direct channel). We use IA based on limited (quantized) CSI sharing to decouple the joint precoder optimization problem into distributed problems which can be tackled at individual transmitters using only local CSI.

The remainder of the paper is organized as follows. In Section II, the system model is described. Distributed precoding methods are discussed in Section III. The proposed distributed methods are presented in Section IV. Simulation results are presented in Section V and conclusions are drawn in Section VI.

Notation: Boldface lowercase and uppercase letters indicate vectors and matrices, respectively. $\mathbf{I}_N$ is the $N \times N$ identity matrix. The trace, conjugate, Hermitian transpose of a matrix or vector are denoted by $\mathrm{tr}(\cdot), (\cdot)^*, (\cdot)^{\mathrm{H}}$ respectively. The expectation operator is represented by $\mathrm{E}(\cdot)$. The Frobenius norm and determinant of a matrix are denoted by $||\cdot||_{\mathrm{F}}$ and $|\cdot|$ respectively. $\mathcal{CN}(0, a)$ denotes the complex Gaussian circularly symmetric distribution with zero mean and variance a.

II. System Model

An interference channel is considered in which K transmitters (base stations) communicate with their respective users over a shared medium. Each BS has M antennas while each user is equipped with N antennas. Data symbols are spatially precoded at the BSs. The number of data streams sent by each BS to its corresponding user is d. The received signal at user

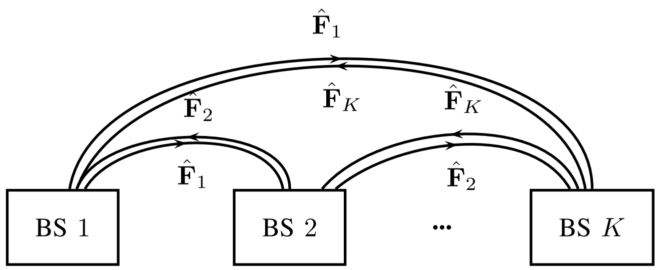

Fig. 1. CSIT sharing

i is denoted by

$$\mathbf{y}_i = \mathbf{H}_{ii}\mathbf{V}_i\mathbf{x}_i + \sum_{j=1, j\neq i}^{K} \mathbf{H}_{ij}\mathbf{V}_j\mathbf{x}_j + \mathbf{n}_i \tag{1}$$

in which $\mathbf{H}_{ij} \in \mathbb{C}^{N\times M}$ is the channel matrix between BS j and user i, $\mathbf{V}_j \in \mathbb{C}^{M\times d}$ and $\mathbf{x}_j \in \mathbb{C}^d$ are the precoding matrix and the data vector of BS j, respectively. Furthermore, $\mathbf{n}_i$ is the additive noise at user i whose entries are distributed according to $\mathcal{CN}(0,1)$. Assuming $\mathrm{E}\left[\mathbf{x}_j\mathbf{x}_j^{\mathrm{H}}\right] = \mathbf{I}_d,\ j = 1,\ldots,K$, the covariance matrix of the signal transmitted by user j is given as $\mathbf{Q}_j = \mathbf{V}_j\mathbf{V}_j^{\mathrm{H}}$ in which the transmit power for user j is $\mathrm{tr}\left(\mathbf{Q}_j\right) = P_j$. We further assume that the elements of the data symbol are i.i.d. Gaussian random variables. The channels are modeled as

$$\mathbf{H}_{ij} = \sqrt{\gamma_{ij}}\tilde{\mathbf{H}}_{ij} \tag{2}$$

where $\tilde{\mathbf{H}}_{ij} \in \mathbb{C}^{N\times M}$ has i.i.d. elements from $\mathcal{CN}(0,1)$ and γ_{ij} denotes the slow-varying shadowing and path loss attenuation. TDD transmission is adopted which enables the BSs to estimate their channels toward different users exploiting the reciprocity of the channel in the uplink phase.

III. Distributed precoding methods

In this section we discuss possible methods to design precoders distributedly at the transmitters. By reciprocity of the channels, the jth BS estimates the channel matrices $\mathbf{H}_{ij},\ i = 1,...,K\,,\, i \neq j$ from the uplink phase. Here, we assume that $\mathbf{H}_{ij},\ i = 1,...,K\,,\, i \neq j$ are known perfectly at BS j. We assume that each BS shares a quantized version of its channels ($\hat{\mathbf{H}}_{ij}$) with other BSs via finite capacity links. Therefore all the quantized CSI ($\{\hat{\mathbf{H}}_{ij}, \forall i,j\}$) is available at all BSs (assuming error-free links). We wish to maximize the sum mutual information for any given channel realization:

$$\max_{\{\mathbf{V}_i\}_{i=1}^K,\, \mathrm{tr}(\mathbf{V}_i\mathbf{V}_i^{\mathrm{H}})=P_i} \sum_{i=1}^{K} \mathcal{I}(\mathbf{x}_i, \mathbf{y}_i). \tag{3}$$

In general (3) is a non-convex problem and the known solutions are sub-optimal and mostly based on iterative algorithms. Moreover, to have a distributed implementation, (3) has to be solved independently at each transmitter which necessitates global CSI (or other types of global information) which has to be identical at all the nodes. Since most of the (close to optimal) solutions are based on iterative algorithms, slightly different CSI at different nodes might result in a totally different set of precoders. Even in special cases where closed form solutions exist (like doing IA in 3-user IC), designing the precoders based on different CSI quality would result in a poor performance [8]. In a practical scenario where CSI is quantized and exchanged between the BSs, one viable option is that all the BSs design the precoders based on the common knowledge of the whole quantized channels. Under this assumption, the BSs should not use their own accurate CSI because the others only have a quantized version of that CSI. Based on the common CSI, every BS will be able to compute its precoder based on a previously agreed method, assuming that the quantized CSI is the true CSI. Different performance metrics can be employed similar to the perfect CSI scenario. Most of the known methods require all the channel matrices between any pair of nodes (for example iterative sum-rate maximization or MSE minimization algorithms). On the other hand, interference alignment does not require the direct channel matrices. Even though IA has poor performance at low SNR, it needs less CSI exchange between the BSs which allows us to quantize more accurately given a backhaul link with a certain capacity. Moreover, it is shown in [9] that one can further reduce CSI sharing requirements when using IA. This prompts us to use IA as a starting point and look for further improvements by taking advantage of the accurate local CSI at each BS in a second step.

IV. Proposed scheme

Assuming that precoders are designed based on the shared knowledge at the BSs, the main issue is that if one BS modifies its own precoder to improve its performance by using its local CSI, the others do not have access to the new precoder of that BS and therefore cannot perform their own optimization. One could think of having a fixed interference space at each receiver and asking the transmitters to create interference only in those spaces. However, this reduces the DoF that can be achieved over the network. Here we use the IA projection filters (designed by using quantized CSI) to fix the interference space at the receivers. After fixing the receive interference space we can look for improving the performance using the local accurate CSI. For example if we employ a rate maximization after fixing the interference spaces, we can ensure the achievability of DoF that could be achieved by the quantized CSI and additionally have an improvement in the sum-rate. We start by solving IA for the quantized CSI $\hat{\mathbf{H}}_{ij}$ (assuming a feasible IA setting), i.e., finding full rank precoding matrices $\mathbf{V}_j^{\mathrm{IA}},\ j = 1,...,K$ and projection matrices $\mathbf{U}_i^{\mathrm{IA}} \in \mathbb{C}^{N\times d},\ i = 1,...,K$ such that

$$\mathbf{U}_i^{\mathrm{IA}\,\mathrm{H}}\hat{\mathbf{H}}_{ij}\mathbf{V}_j^{\mathrm{IA}} = \mathbf{0} \qquad \forall i,j \in \{1,...,K\},\ j \neq i, \tag{4}$$

$$\mathrm{rank}(\mathbf{U}_i^{\mathrm{IA}\,\mathrm{H}}\hat{\mathbf{H}}_{ii}\mathbf{V}_i^{\mathrm{IA}}) = d. \tag{5}$$

It was shown in [9] that IA can be solved at the BSs if every BS transmits to all others a point on the Grassmann manifold $\mathcal{G}_{(K-1)N,M}$ representing the column space of $\mathbf{H}_j = [\mathbf{H}_{1,j}^{\mathrm{H}}, ..., \mathbf{H}_{j-1,j}^{\mathrm{H}}, \mathbf{H}_{j+1,j}^{\mathrm{H}}, ..., \mathbf{H}_{K,j}^{\mathrm{H}}]^{\mathrm{H}}$ which is a $(K-1)N \times M$ matrix. Let $\mathbf{F}_j$ denote an orthonormal basis for the column space of $\mathbf{H}_j$. We assume that BS j will quantize $\mathbf{F}_j$ over the Grassmann manifold (see [9] for details) and send the quantized version of $\mathbf{F}_j$ (denoted by $\hat{\mathbf{F}}_j$) to the other BSs as shown in Fig. 1. Then, every BS will design the IA precoders ($\mathbf{V}_i^{\mathrm{IA}}$) and receive filters ($\mathbf{U}_i^{\mathrm{IA}}$) based on the common knowledge, i.e., $\{\hat{\mathbf{F}}_j\}_{j=1}^K$.

Fixing the receive filters decouples the problem (3). It remains to solve how to design precoders locally assuming fixed receive filters $\mathbf{U}_i^{\mathrm{IA}}$ for the users, using the locally available CSI. We now present two possible solutions:

A. MSE minimization

Let us first consider the following MMSE problem

$$\min_{\{\mathbf{V}_i\}_{i=1}^K, \mathrm{tr}(\mathbf{V}_i\mathbf{V}_i^{\mathrm{H}})=P_i} \sum_{i=1}^K \mathrm{E}(||\mu_i \mathbf{A}_i \mathbf{x}_i - \mathbf{U}_i^{\mathrm{IA}^{\mathrm{H}}} \mathbf{y}_i||_{\mathrm{F}}^2) \tag{6}$$

where $\mathbf{A}_i = \mathbf{U}_i^{\mathrm{IA}^{\mathrm{H}}} \mathbf{H}_{ii} \mathbf{V}_i^{\mathrm{IA}}$ and μ_i is a constant. The considered metric is based on approaching (in the mean-square error sense) $\mu_i \mathbf{A}_i \mathbf{x}_i$, which is a scaled version of the signal of interest obtained when using the IA precoders and projection filters computed from the estimated CSI. By taking the Lagrangian of the objective function in (6), it can be shown that the set of precoders that optimize (6) have the form $\mathbf{V}_j = \mu_j \mathbf{V}_j^{\star}$ with

$$\mathbf{V}_j^{\star} = (\sum_{i=1}^K \bar{\mathbf{H}}_{ij}^{\mathrm{H}} \bar{\mathbf{H}}_{ij} + \omega_j \mathbf{I}_M)^{-1} \bar{\mathbf{H}}_{jj}^{\mathrm{H}} \mathbf{A}_j \tag{7}$$

where $\bar{\mathbf{H}}_{ij} = \mathbf{U}_i^{\mathrm{IA}^{\mathrm{H}}} \mathbf{H}_{ij}, \forall i, j$ are the equivalent channel matrices after projection with the IA receive filters. ω_j is the Lagrangian multiplier associated with the power constraint $\mathrm{tr}(\mathbf{V}_j \mathbf{V}_j^{\mathrm{H}}) = P_j$. The optimal values for $\omega_j, \mu_j, \forall j$ do not have a closed form solution for individual power constraints. Moreover, finding the optimal values requires global CSI. Here we pick those values heuristically as follows

$$\omega_j = \frac{a_j}{P_j}, \quad \mu_j = \sqrt{\frac{P_j}{\mathrm{tr}(\mathbf{V}_j^{\star} \mathbf{V}_j^{\star \mathrm{H}})}}, \ \forall j \tag{8}$$

for some constant values a_j. Note that with this particular choice of μ_j, the power constraints are satisfied. At low SNR, the identity matrix is dominant which results in an egoistic transmission. At high SNR, the interference created for other receivers becomes significant and the altruistic precoding becomes preferable (which is obtained as $\omega_j \to 0$). Note however that this scheme is not expected to be optimal at low SNR since only d modes are used while at low SNR the optimal transmission scheme uses all available modes.

To summarize, we solve IA at all BSs based on the quantized CSI available globally and afterwards, every BS fixes the receive filters with the receive filters computed by IA and finds its MSE minimizing precoder $\mathbf{V}_j = \mu_j \mathbf{V}_j^{\star}$ according to (7), (8), approximately solving (6).

B. Approximate sum-rate maximization

Let us denote $\mathbf{Q}_S^i = \bar{\mathbf{H}}_{ii} \mathbf{Q}_i \bar{\mathbf{H}}_{ii}^{\mathrm{H}}$ and $\mathbf{Q}_I^i = \sum_{j=1, j\neq i}^K \mathbf{Q}_I^{ij} = \sum_{j=1, j\neq i}^K \bar{\mathbf{H}}_{ij} \mathbf{Q}_j \bar{\mathbf{H}}_{ij}^{\mathrm{H}}$ the covariance matrices of the desired signal and interference after projecting by the IA receive filter respectively.

After projection with the IA receive filters, sum-rate can be written as,

$$\bar{R}_{\mathrm{sum}} = \sum_{i=1}^K \left[\log \left| \mathbf{I}_d + \mathbf{Q}_S^i + \mathbf{Q}_I^i \right| - \log \left| \mathbf{I}_d + \mathbf{Q}_I^i \right| \right] \tag{9}$$

We consider the following objective function

$$\begin{aligned} &\max_{\mathbf{Q}_1, ..., \mathbf{Q}_K} \bar{R}_{\mathrm{sum}} \\ &\text{s.t.} \qquad \mathrm{tr}(\mathbf{Q}_j) = P_j \quad \forall \ j = 1, ..., K. \end{aligned} \tag{10}$$

The first term in (9) can be approximated as

$$\log \left| \mathbf{I}_d + \mathbf{Q}_S^j + \mathbf{Q}_I^j \right| \approx \log \left| \mathbf{I}_d + \mathbf{Q}_S^j \right| \tag{11}$$

where the approximation comes from the fact that by interference alignment (even though based on quantized CSI), the interference power inside the desired signal space is reduced significantly, i.e., $\mathbf{Q}_I^i$ is negligible compared to $\mathbf{Q}_S^i$. Therefore

$$\bar{R}_{\mathrm{sum}} \approx \sum_{i=1}^K \left[\log \left| \mathbf{I}_d + \mathbf{Q}_S^i \right| - \log \left| \mathbf{I}_d + \mathbf{Q}_I^i \right| \right]. \tag{12}$$

From the concavity of log function, Jensen's inequality gives

$$\log \left| \mathbf{I}_d + \mathbf{Q}_I^i \right| \geq \frac{1}{K-1} \sum_{j=1, j\neq i}^K \log \left| \mathbf{I}_d + (K-1) \mathbf{Q}_I^{ij} \right|. \tag{13}$$

Therefore we get

$$\bar{R}_{\mathrm{sum}} \leq \sum_{j=1}^K \tilde{R}_j, \tag{14}$$

where

$$\tilde{R}_j = \log \left| \mathbf{I}_d + \mathbf{Q}_S^j \right| - \sum_{i=1, i\neq j}^K \frac{\log \left| \mathbf{I}_d + (K-1) \mathbf{Q}_I^{ij} \right|}{K-1}. \tag{15}$$

Clearly each $\tilde{R}_j$ is only a function of $\mathbf{Q}_j$ and the outgoing channels from BS j. Therefore the optimization problem in (10) can be approximately decoupled into the following K distributed optimization problems :

$$\begin{aligned} &\max_{\mathbf{Q}_j} \tilde{R}_j \qquad \forall \ j = 1, ..., K \\ &\text{s.t.} \quad \mathrm{tr}(\mathbf{Q}_j) = P_j, \end{aligned} \tag{16}$$

Clearly we are optimizing an upper bound of the sum rate which is suboptimal. Here, we propose to use a gradient ascent method to determine a local maximum of $\tilde{R}_j$ as summarized in Algorithm 1. The gradient ascent algorithm consists in starting from an arbitrary initial covariance matrix $\mathbf{Q}_j = \mathbf{Q}_j^{(0)}$, calculating the gradient matrix and moving in the gradient direction with some step size, which gives a new covariance matrix $\mathbf{Q}^1$. The algorithm unfolds similarly as in the initial step until convergence.

Algorithm 1 Iterative optimization at BS j

Find the IA solution $\{\mathbf{U}_i^{\mathrm{IA}}, \mathbf{V}_i^{\mathrm{IA}}\}_{i=1}^K$, based on $\{\hat{\mathbf{F}}_j\}_{j=1}^K$.
Calculate the equivalent channels, $\bar{\mathbf{H}}_{ij} = \mathbf{U}_i^{\mathrm{IA}^{\mathrm{H}}}\mathbf{H}_{ij}, \forall i$.
Initialization: $m = 0$ and $\mathbf{Q}_j^{(0)}$ arbitrary.
Repeat

- Evaluate the gradient w.r.t. $\mathbf{V}_j$, $\nabla_j \tilde{R}_j$
- Let $\mathbf{V}_j = \mathbf{V}_j + \beta\nabla_j\tilde{R}_j$ (for some step-size β)
- Let $\mathbf{Q}_j^{(m+1)} = P_j \frac{\mathbf{V}_j\mathbf{V}_j^{\mathrm{H}}}{\mathrm{tr}(\mathbf{V}_j\mathbf{V}_j^{\mathrm{H}})}$
- $m \leftarrow m+1$

until convergence.

We now derive the expression of the gradient w.r.t. the precoders. The optimization finds the precoding matrix $\mathbf{V}_j$ such that $\sqrt{\frac{P_j}{\mathrm{tr}(\mathbf{V}_j\mathbf{V}_j^{\mathrm{H}})}}\mathbf{V}_j$ maximizes the objective function at BS j and therefore the transmit power constraint is always satisfied. The gradient of $\tilde{R}_j$ w.r.t. $\mathbf{V}_j$ is calculated as

$$\nabla_j\tilde{R}_j = \eta_j(\mathbf{\Omega}_j - \alpha_j\mathbf{I}_M)\mathbf{V}_j \tag{17}$$

where $\alpha_j = \frac{\mathrm{tr}(\mathbf{\Omega}_j\mathbf{V}_j\mathbf{V}_j^{\mathrm{H}})}{\mathrm{tr}(\mathbf{V}_j\mathbf{V}_j^{\mathrm{H}})}$ and

$$\mathbf{\Omega}_j = \bar{\mathbf{H}}_{jj}^{\mathrm{H}}(\mathbf{I}_d+\mathbf{Q}_S^j)^{-1}\bar{\mathbf{H}}_{jj} - \sum_{i=1,i\neq j}^{K}\bar{\mathbf{H}}_{ij}^{\mathrm{H}}(\mathbf{I}_d+(K-1)\mathbf{Q}_I^{ij})^{-1}\bar{\mathbf{H}}_{ij}. \tag{18}$$

Considering one stream IA, instead of running Algorithm 1, one can try to find a solution for $\nabla_j\tilde{R}_j = 0$ as follows:

$$\begin{aligned}&\bar{\mathbf{H}}_{jj}^{\mathrm{H}}(\mathbf{I}_d+\mathbf{Q}_S^j)^{-1}\bar{\mathbf{H}}_{jj}\mathbf{V}_j\\ &= \big(\alpha_j\mathbf{I}_M + \sum_{i=1,i\neq j}^{K}\bar{\mathbf{H}}_{ij}^{\mathrm{H}}(\mathbf{I}_d+(K-1)\mathbf{Q}_I^{ij})^{-1}\bar{\mathbf{H}}_{ij}\big)\mathbf{V}_j\end{aligned} \tag{19}$$

therefore

$$\begin{aligned}\mathbf{V}_j = &\big(\alpha_j\mathbf{I}_M + \sum_{i=1,i\neq j}^{K}\bar{\mathbf{H}}_{ij}^{\mathrm{H}}(\mathbf{I}_d+(K-1)\mathbf{Q}_I^{ij})^{-1}\bar{\mathbf{H}}_{ij}\big)^{-1}\\ &\times\bar{\mathbf{H}}_{jj}^{\mathrm{H}}(\mathbf{I}_d+\mathbf{Q}_S^j)^{-1}\bar{\mathbf{H}}_{jj}\mathbf{V}_j.\end{aligned} \tag{20}$$

Now we initialize the precoder $\mathbf{V}_j$ (which is a vector in this case), update $\mathbf{Q}_S^j, \mathbf{Q}_I^{ij}$ and iteratively find new precoders according to (20).

V. Simulation Results

In this section, the performance of the proposed scheme is evaluated through numerical simulations. The performance metric is the sum rate evaluated through Monte-Carlo simulations using the precoders designed in Section IV. A three-user IC is considered. Entries of the channel matrices are generated according to $\mathcal{CN}(0,\gamma_{ij})$ (where γ_{ij} is the path-loss coefficient for the interfering channel between BS j and user i) and the performance results are averaged over the channel realizations. In all simulations, the direct links are assumed to have no path-loss, i.e., $\gamma_{ii} = 1, \forall i$. Our proposed methods are compared to IA with quantized CSI according to the technique in [9] and maximum sum rate algorithm [2] with quantized CSI where the channels are vectorized and quantized using RVQ. Figures 2-4 show the achievable sum rate versus transmit SNR when each BS is allowed to share N_b bits with the other BSs for different antenna configurations and different number of bits. For the quantization phase in the proposed scheme (and also IA with quantized CSI method), instead of the optimal subspace packing codebook, a random codebook is used where the codebook entries are independent random truncated unitary matrices generated from the Haar distribution. For the method of maximum sum rate with quantized CSI, the channel matrices are vectorized, normalized and quantized using random unit norm vectors. In this method, in order to simplify the quantization, we assume that the norm of the vectors are known at all the BSs perfectly. The eigen water filling method is also presented as another baseline in which the BSs maximize their rate selfishly using only the knowledge of their direct channel and treating interference as noise. Furthermore, the results are also benchmarked against the time sharing method denoted by "Orthogonal channel access" in the figures. Clearly the proposed scheme outperforms the other methods for the same number of bits in a wide range of practical SNRs.

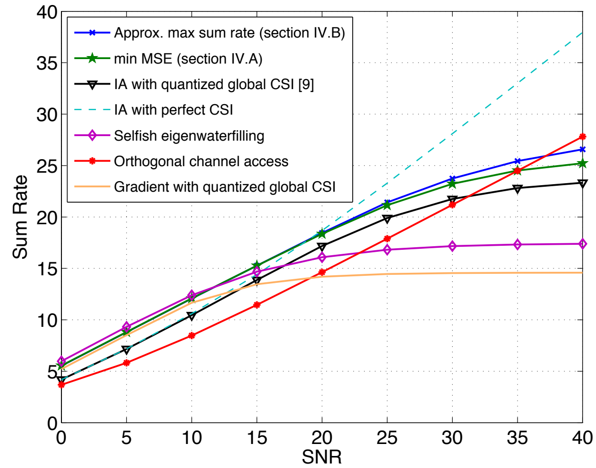

Fig. 2. Comparison of sum-rate for $K = 3, M = N = 2, d = 1, N_b = 12$ and 10 dB path loss for interfering links

VI. Conclusion

Interference alignment for cellular downlink was investigated and methods were proposed to improve the performance by exploiting the local CSI available at each transmitter. We employed efficient information exchange among interfering transmitters over backhaul links in order to design IA precoders. Using the IA solution, we devised distributed optimiza-

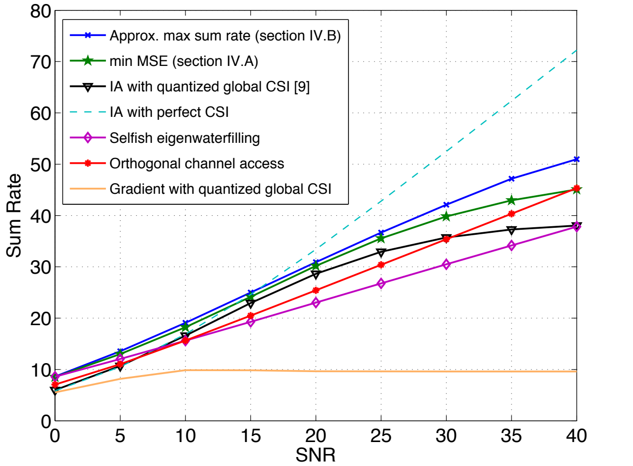

Fig. 3. Comparison of sum-rate for $K = 3, M = 5, N = 3, d = 2, N_b = 12$ and 3 dB path loss for interfering links

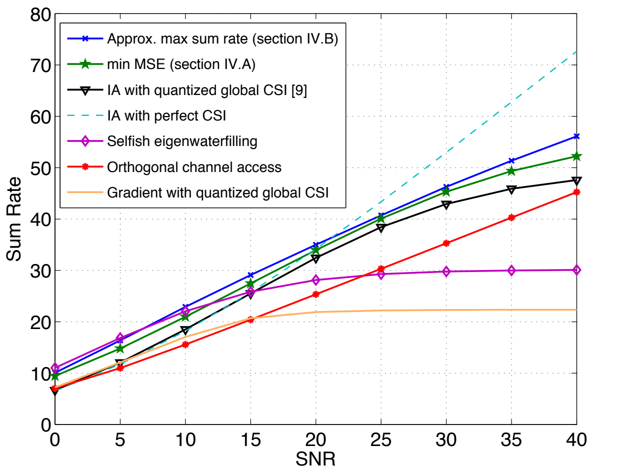

Fig. 4. Comparison of sum-rate for $K = 3, M = 5, N = 3, d = 2, N_b = 9$ and 10 dB path loss for interfering links

tion problems to compute improved precoders independently at each transmitter.

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